REMARKS

I. Introduction

In response to the Office Action dated October 4, 2006, claims 1, 8 and 15 have been amended. Claims 1-21 remain in the application. Re-examination and re-consideration of the application, as amended, is requested.

II. Claim Amendments

Applicants' attorney has made amendments to the claims as indicated above. These amendments were made solely for the purpose of clarifying the language of the claims, and were not required for patentability or to distinguish the claims over the prior art.

III. Statutory Subject Matter Rejection

In section (2) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §101 as being directed to non-statutory subject matter. The Office Action asserts that claims 1-21 do not recite a "concrete and tangible result, that a process that consists solely of the manipulation of an abstract idea is not concrete or tangible, and that Applicants' claims are simply manipulating and doing mathematical operations without a "concrete and tangible result."

Applicants' attorney has amended the claims to overcome these rejections.

However, should issues still remain in this regard, Applicants' attorney requests that the Examiner indicate how the rejection can be overcome, in accordance with the directives of the Interim Guidelines for Examination of Patent Applications for Patent Subject Matter Eligibility (Guidelines) II. See also M.P.E.P. § 2106. Specifically, should it be necessary, the Applicants' attorney requests that the Examiner identify features of the invention that would render the claimed subject matter statutory if recited in the claim. See Guidelines IV.B. See also M.P.E.P. § 2106.

IV. Rejections under 35 U.S.C. §112, First Paragraph

In paragraph (3) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §112, first paragraph, as failing to comply with the enablement requirement, wherein the Office Action asserts that the claims contains subject matter which was not described in the specification in such a way as to enable one skilled in the art to which it pertains, or with which it is most nearly connected, to make and/or use the invention. In this regard the Office Action states that Applicants' specification

simply recites the language of the claims but is not enabling "in how to determine the likelihood that a customer would respond to a future advertisement campaign."

Applicants' attorney traverses these rejections.

Applicants' attorney submits that the specification does describe how to make and use the claimed invention. See, for example, the discussion at page 7, line 26 through page 11, line 20, referencing FIG. 3, which is set forth below:

> <u>Response Modeling Service</u>
>
> FIG. 3 is a flowchart that illustrates the steps performed by the Response Modeling service according to the preferred embodiment of the present invention. The Response Modeling Service creates and validates a customer promotion response model that comprises a statistical model that is used to predict the likelihood that a specific customer will respond to a promotional campaign in the future.
>
> In order to create a predictive response model, data describing past behavior must exist on which to base that prediction. To accomplish this, the Response Modeling service utilizes data that is derived from the relational database, either through the Analytic Data Set Creation service or by manual efforts.
>
> Using the data derived from the relational database, the Response Modeling service performs the following functions:
>
> - Automatically create a statistical model that will predict the likelihood a customer will respond to a particular kind of campaign.
> - Automatically score customers in the relational database based on the statistical model.
> - Automatically produce a list of customers that have high propensity to respond based on the scores.
> - Help marketing analysts more accurately predict customer buying behavior based on the scores and understand drivers of product and/or service usage and brand loyalty.
> - Provide a wide range of outputs to help users interpret results, including:
>   - Information about the variables included in the model, including an assessment of the relative importance of the different variables,
>   - Deciling information about customers in the validation sample, which includes an analysis of behavioral and demographic variables for customers in each decile,
>   - Store reports showing the distribution of customers by decile, for each store or store region,
>   - Lift charts showing the expected response to the promotion, by decile and cumulatively, and
>   - Statistical measures, including those that compare the current model to other models stored in a model database.
> - Provide a model database where models are stored, along with statistics evaluating model quality and descriptive information about the model.

- Provide the ability to compare models and their predictive capabilities.

The steps performed by the Response Modeling service are illustrated in FIG. 3, and include the definition of the input data, model estimation, model validation, and customer scoring.

The definition of the input data for the response model is perhaps the most critical step in the entire process (Block 300). Generally, the input data is comprised of a set of Analytic Variables that are subdivided into independent and dependent variables, wherein the dependent variables are also known as response variables. These Analytic Variables are statistically tested to determine which variables, if any, are significant in differentiating actual responders from non-responders to a past event.

Once selected, the input data set is split into two samples: a test or training sample and a validation or holdout sample (Block 302). This split is based on a stratified random sample of customers from the input data with the largest portion, e.g., 70%, being reserved for the test sample and the remainder, e.g., 30%, being reserved for the validation sample.

The Response Modeling service then identifies related independent and dependent variables using the test sample, in order to create a response model that best predicts the likelihood of a response from a customer, given the knowledge of actual responses to past promotional campaigns (Block 304). This is accomplished by the Response Modeling service examining each of the independent variables and attempting to identify the related dependent variables, in order to determine which of these variables has a significant impact in differentiating responders from non-responders. The Response Modeling separates the predictive variables from the others. The selected Analytic Variables comprise the response model, and this model is likely to contain fewer Analytic Variables than are contained in the input data.

The Response Modeling service then identifies a Transformation Type for the identified related independent and dependent variables, i.e., the predictive variables (Block 306). The Transformation Type is a mathematical operation that provides the strongest association between the identified related independent variable and the dependent variables. Possible transformation types are listed in the following Table, although this list is not intended to be exhaustive and other transformations may be used as well.

Transformation Type	Definition
None	X
Square	X^2
Square Root + 1	$(X + 1)^{1/2}$
Cube	X^3
Cube root + 1	$(X + 1)^{1/3}$
Natural Log Function + 1	$\ln(X + 1)$
Exponential Function + 1	$e^{(X+1)}$
Inverse + 1	$1/(X + 1)$
Z Score	(X – Average (X)) / Standard Deviation of X

After identifying a Transformation Type, the Response Modeling service estimates a Coefficient, or weight, for each of the identified related independent and dependent variables found to be significant in predicting the likelihood of response (Block 308). The Coefficient is a relative measure of the contribution of a variable to the likelihood of response. However, the size of the Coefficient does not indicate the relative importance of the variable in predicting the likelihood of response, since it is itself dependent on the magnitude of the variable. The sign of the Coefficient indicates whether the independent variable is positively or negatively correlated with the dependent variable.

After estimating a Coefficient, the Response Modeling service generates a Model Equation that is a mathematical representation of the association of the identified related independent and dependent variables that result in a statistical best fit of known responders versus non-responders (Block 310). Specifically, the Model Equation includes an association of the independent variable with the dependent variable that best differentiates responders from non-responders, as well as the Transformation Type and the Coefficients associated with the variables.

The Response Modeling service applies the Model Equation to the validation sample, in order to validate the predictability of the response model (Block 312). This step validates the Model Equation by comparing a predicted likelihood of response with an actual response. The Response Modeling service provides extensive outputs that can be employed by users to determine the validity of the model from an analytic perspective.

If the validation of the Model Equation is satisfactory, the user can choose to score customers retrieved from the relational database for a future campaign (Block 314). Scoring a customer differs from model validation in that the Model Equation is applied to a segment of customers retrieved from the relational database for a future campaign, rather than a past campaign. For example, the customers that are scored do not have to include anyone who was part of the past campaign. Thereafter, the user can select a customer segment for a future campaign based on the scores of the customers in the segment, as well as on any other attribute. Selecting only those people with the highest likelihood to respond, (e.g., with the highest scores), allows the user to reduce the number of people targeted in the promotional campaign, while increasing the number of responders. It also allows the user to select effectively from a different pool of people. As a result, costs are reduced.

The automatic Response Modeling service provides many advantages over traditional approaches to creating and using promotion response models. For example, the Response Modeling service generates statistical models quicker and less expensively than manual modeling, thereby making it feasible to create a more extensive set of models. Moreover, the Response Modeling service develops the models using the most current data for estimating behavior, lessening the concern about model obsolescence. In addition, users of the Response Modeling service can more easily test out alternative promotion campaigns and score alternative customer segments, both of which can be assessed in terms of expected response.

The above portions of Applicants' specification do describe how to make and use Applicants' claimed invention, and describe all the limitations found in Applicants' claims.

Moreover, the assertion that Applicants' specification is not enabling in how to "determine the likelihood that a customer would respond to a future advertisement campaign," is erroneous, because nowhere can this limitation be found in Applicants' claims. See M.P.E.P. §2163-2164.

Consequently, Applicants' attorney requests that the rejections be withdrawn.

V. Rejections under 35 U.S.C. §112, Second Paragraph

In paragraph (4) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §112, second paragraph, as being indefinite for failing to particularly point out and distinctly claim the subject matter which Applicants regard as the invention. The Office Action states that the claims recites an independent and a dependent variable but do not clearly describe the difference between said variables, and that the limitation would be interpreted as users profile data. Also, the Office Action states that the claims recite "estimating a coefficient for each of the identified related independent and dependent variables," and that the limitation would be interpreted as a scalar obtained from a function. In addition, the Office Action states that claim 5 recites "statistical best fit of known responder versus non-responder," and that the limitation would be interpreted as meaning determining a prediction of customers that would respond to an advertising campaign.

Applicants' attorney traverses these rejections.

With regard to "independent and dependent variables," the Office Action errs in asserting that these is no difference between the variables, and that the limitation should be interpreted as "users profile data." Applicants' attorney notes that the definition of independent variable is "a variable that does not depend on another variable," and the definition of dependent variable is "a variable that does depend on another variable," i.e., a dependent variable may be predicted by or caused by independent variables.

Moreover, the "independent and dependent variables" are referred to throughout Applicants' specification in the following manner:

> Applicants' Specification: Page 9, line 1 - page 11, line 20
>
> The steps performed by the Response Modeling service are illustrated in FIG. 3, and include the definition of the input data, model estimation, model validation, and customer scoring.
>
> The definition of the input data for the response model is perhaps the most critical step in the entire process (Block 300). **Generally, the input data is comprised of a set of Analytic Variables that are subdivided into independent**

and dependent variables, wherein the dependent variables are also known as response variables. These Analytic Variables are statistically tested to determine which variables, if any, are significant in differentiating actual responders from non-responders to a past event.

Once selected, the input data set is split into two samples: a test or training sample and a validation or holdout sample (Block 302). This split is based on a stratified random sample of customers from the input data with the largest portion, e.g., 70%, being reserved for the test sample and the remainder, e.g., 30%, being reserved for the validation sample.

The Response Modeling service then identifies related independent and dependent variables using the test sample, in order to create a response model that best predicts the likelihood of a response from a customer, given the knowledge of actual responses to past promotional campaigns (Block 304). This is accomplished by the Response Modeling service examining each of the independent variables and attempting to identify the related dependent variables, in order to determine which of these variables has a significant impact in differentiating responders from non-responders. The Response Modeling separates the predictive variables from the others. The selected Analytic Variables comprise the response model, and this model is likely to contain fewer Analytic Variables than are contained in the input data.

The Response Modeling service then identifies a Transformation Type for the identified related independent and dependent variables, i.e., the predictive variables (Block 306). The Transformation Type is a mathematical operation that provides the strongest association between the identified related independent variable and the dependent variables. Possible transformation types are listed in the following Table, although this list is not intended to be exhaustive and other transformations may be used as well.

Transformation Type	Definition
None	X
Square	X^2
Square Root + 1	$(X + 1)^{1/2}$
Cube	X^3
Cube root + 1	$(X + 1)^{1/3}$
Natural Log Function + 1	$\ln(X + 1)$
Exponential Function + 1	$e^{(X+1)}$
Inverse + 1	$1/(X + 1)$
Z Score	$(X - \text{Average}(X)) / \text{Standard Deviation of } X$

After identifying a Transformation Type, the Response Modeling service estimates a Coefficient, or weight, for each of the identified related independent and dependent variables found to be significant in predicting the likelihood of response (Block 308). The Coefficient is a relative measure of the contribution of a variable to the likelihood of response. However, the size of the Coefficient does not indicate the relative importance of the variable in predicting the likelihood of response, since it is itself dependent on the magnitude of the variable.

The sign of the Coefficient indicates whether the independent variable is positively or negatively correlated with the dependent variable.

After estimating a Coefficient, the Response Modeling service generates a Model Equation that is a mathematical representation of the association of the identified related independent and dependent variables that result in a statistical best fit of known responders versus non-responders (Block 310). Specifically, the Model Equation includes an association of the independent variable with the dependent variable that best differentiates responders from non-responders, as well as the Transformation Type and the Coefficients associated with the variables.

The Response Modeling service applies the Model Equation to the validation sample, in order to validate the predictability of the response model (Block 312). This step validates the Model Equation by comparing a predicted likelihood of response with an actual response. The Response Modeling service provides extensive outputs that can be employed by users to determine the validity of the model from an analytic perspective.

If the validation of the Model Equation is satisfactory, the user can choose to score customers retrieved from the relational database for a future campaign (Block 314). Scoring a customer differs from model validation in that the Model Equation is applied to a segment of customers retrieved from the relational database for a future campaign, rather than a past campaign. For example, the customers that are scored do not have to include anyone who was part of the past campaign. Thereafter, the user can select a customer segment for a future campaign based on the scores of the customers in the segment, as well as on any other attribute. Selecting only those people with the highest likelihood to respond, (e.g., with the highest scores), allows the user to reduce the number of people targeted in the promotional campaign, while increasing the number of responders. It also allows the user to select effectively from a different pool of people. As a result, costs are reduced.

The automatic Response Modeling service provides many advantages over traditional approaches to creating and using promotion response models. For example, the Response Modeling service generates statistical models quicker and less expensively than manual modeling, thereby making it feasible to create a more extensive set of models. Moreover, the Response Modeling service develops the models using the most current data for estimating behavior, lessening the concern about model obsolescence. In addition, users of the Response Modeling service can more easily test out alternative promotion campaigns and score alternative customer segments, both of which can be assessed in terms of expected response.

Consequently, Applicants' attorney requests that the rejections be withdrawn.

With regard to "estimating a coefficient for each of the identified related independent and dependent variables," the Office Action errs in asserting that the limitation should be interpreted as "a scalar obtained from a function."

Applicants' attorney notes that "Coefficient" is defined in Applicants' specification in the following manner:

Applicants' Specification: Page 10, line 2 et seq.

After identifying a Transformation Type, the Response Modeling service estimates a Coefficient, or weight, for each of the identified related independent and dependent variables found to be significant in predicting the likelihood of response (Block 308). The Coefficient is a relative measure of the contribution of a variable to the likelihood of response. However, the size of the Coefficient does not indicate the relative importance of the variable in predicting the likelihood of response, since it is itself dependent on the magnitude of the variable. The sign of the Coefficient indicates whether the independent variable is positively or negatively correlated with the dependent variable.

Consequently, Applicants' attorney requests that the rejections be withdrawn.

With regard to claim 5 and the recitation of "statistical best fit of known responder versus non-responder," the Office Action errs in asserting that the limitation should be interpreted as "determining a prediction of customers that would respond to an advertising campaign."

Applicants' attorney notes that "statistical best fit of known responder versus non-responder" is defined in Applicants' specification in the following manner:

Applicants' Specification: Page 10, line 10 et seq.

After estimating a Coefficient, the Response Modeling service generates a Model Equation that is a mathematical representation of the association of the identified related independent and dependent variables that result in a statistical best fit of known responders versus non-responders (Block 310). Specifically, the Model Equation includes an association of the independent variable with the dependent variable that best differentiates responders from non-responders, as well as the Transformation Type and the Coefficients associated with the variables.

Consequently, Applicants' attorney requests that the rejections be withdrawn.

VI. Prior Art Rejections

A. The Office Action Rejections

In paragraph (5) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §102(e) as being anticipated by Cook, U.S. Patent No. 6,631,360 (Cook).

Applicants' attorney respectfully traverses these rejections.

B. The Applicants' Claimed Invention

Independent claims 1, 8 and 15 are generally directed to creating a customer promotion response model for use in customer relationship marketing. Claim 1 is representative and comprises the steps of:

(a) defining an input data set for the response models, wherein the input data set is comprised of one or more Analytic Variables that are subdivided into independent and dependent variables;

(b) splitting the input data set into a test sample and a validation sample;

(c) identifying related independent and dependent variables using the test sample;

(d) identifying a Transformation Type for each of the identified related independent and dependent variables;

(e) estimating a Coefficient for each of the identified related independent and dependent variables;

(f) generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient;

(g) validating the generated Model Equation by applying it to the validation sample; and

(h) scoring customers retrieved from a database stored in the computer using the validated Model Equation as a customer promotion response model for use in customer relationship marketing.

C. The Cook Reference

Cook discloses a computer-implementable method of selecting which engine of a plurality of inference engines to use to predict the categories into which individuals fall, such as buyer/non-buyer, and produce forecast reports based on the predictions. Training (known) sample data that categorizes individuals based on the individual's profile is sequentially applied to multiple inference engines to determine which engine is best based on a desired objective. Then, a classifier associated with the selected engine is used to analyze unknown sample data, create category predictions and produce forecast reports based on the predictions.

D. The Applicants' Claims Are Patentable Over The Reference

Applicants' invention, as recited in independent claims 1, 8 and 15, is patentable over the Cook reference, because the claims recite a specific combination of limitations not found in the Cook reference.

The Office Action, however, asserts that Cook teaches all the elements of the independent claims, as well as all the elements of the dependent claims.

Applicant's attorney disagrees.

For example, the Office Action asserts that Cook teaches "(b) splitting the input data set into a test sample and a validation sample," at col. 10, line 55 - col. 11, line 20, which is set forth below:

> Returning to FIG. 4A, after the first inference engine is selected, a set of profile features are selected 409. This step is included so that independent variables (individual profile features) that are not different among categories can be eliminated. Preferably individual profile features are sorted based on standard statistics after controlling for multicolinearities. In addition to eliminating independent variables for which there is insufficient data for estimation, less significant individual profile features can also be eliminated if desired. The end result is one or more sets of profile features. At step 409 one set is selected.
>
> After the inference engine and set of profile features have been selected, a training process is conducted 411. An example of a training process formed in accordance with the invention is illustrated in FIG. 6 and described below. In general, during the training process, various probability density functions are estimated for the selected engine and a data structure containing unbiased density values is created.

Applicants' attorney notes that the cited location in Cook merely describes a training process, but says nothing about splitting an input data set into a test sample and a validation sample.

In another example, the Office Action asserts that Cook teaches "(c) identifying related independent and dependent variables using the test sample," at col. 12, lines 5-45, which is set forth below:

> FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more

> likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.
>
> After the data sources have been identified, a training sample set is established 507. This involves downloading data from the data source(s) and assembling the data into a computer file, or set of computer files, in a specific format, and storing the files in a workspace, i.e., in temporary memory. After establishing a training set in this matter, the downloaded data is converted into a training data structure having a predetermined configuration and the training data structure is stored in memory 509. A suitable training data structure is illustrated in FIG. 11. The profile features 1111a, 1111b, 1111c . . . 1111n of each individual 1113 in each category 1115 are included in the training data structure. As illustrated in FIG. 4A and discussed above, after the training data structure has been created, selected features of individuals may be eliminated. See step 409, FIG. 4A.

Applicants' attorney notes that the cited location in Cook merely describes selecting categories (such as responder/non-responder), identifying data sources for the selected categories, and downloading data from the data sources to a training sample set, but says nothing about identifying related independent and dependent variables using the test sample. Indeed, it appears that Cook identifies the responder/non-responder <u>before</u> creating the training sample.

In yet another example, the Office Action asserts that Cook teaches "(d) identifying a Transformation Type for each of the identified related independent and dependent variables," i.e., an estimated density function, at col. 11, lines 20-65, which is set forth below:

> After the calibration process has been completed for the selected engine, a test 415 is made to determine if any more sets of features need to be processed for the selected inference engine. If so, the next set of features is selected and the training and calibration processes 411 and 413 are repeated. If no more sets of features need to be processed, the set of features for the selected engine that best meets the desired objective are selected 417. Then a test is made to determine if any additional inference engines are to be selected. If so, as shown by decision block 415, the foregoing process is repeated, i.e., another inference engine is selected 409, a set of features is selected 409, and the training process is performed 411, followed by the calibration process 413. The foregoing sequence is repeated until no more inference engines remain to be selected.
>
> Preferably, as each inference engine is processed, the resulting decision array is analyzed during the calibration step to determine if the current inference engine is

> better than previously processed inference engines. If so, the array and the estimated density function for the current inference engine replace previously stored decision array and estimated density function data. If the current inference engine is not better, the previously stored decision array and the estimated density function data is retained and this data for the current inference engine is discarded. Thus, after the training and calibration processes are complete for all inference engines, the decision array and estimated density function for the best inference engine are stored.
>
> After the best inference engine has been selected in the foregoing manner, a sample comprising individual observations for which category membership is unknown is identified. The unknown sample contains the same independent variables (individual profile features) as did the training sample and is set up 421 in generally the same manner as the training sample was set up 401. An example of an unknown sample setup process formed in accordance with this invention is illustrated in FIG. 9 and described below. Thereafter, each individual in the unknown sample is assigned to a category using the previously developed and stored estimated density function associated with the selected best inference engine. Each such assignment is called a prediction. The predictions are tallied and the tally adjusted for error rates determined by the decision array created during the calibration process described above. The result is a forecast. See block 423. Next, a test 425 is made to determine if another unknown sample is to be analyzed. If so, the foregoing steps are repeated. After all unknown samples have been examined, the user can determine 427 if the objective needs to be reset. If the objective needs to be reset, the objective is reset and the entire process is repeated. If not, the process ends.

Applicants' attorney notes that the cited location in Cook merely describes selecting among inference engines, which are algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function. However, a density function is not a Transformation Type, which is defined as a mathematical operation that provides the strongest association between the identified related independent variable and the dependent variables.

In still another example, the Office Action asserts that Cook teaches "(e) estimating a Coefficient for each of the identified related independent and dependent variables," i.e., a scalar is obtained, at col. 13, lines 5-45, which is set forth below:

> As noted above, FIG. 7 illustrates a density function and density value calculating process 605 suitable for use in the process illustrated in FIG. 6 formed in accordance with the invention. First, a category is selected 701 by, for example, setting a pointer to the memory location of the data associated with the selection--in this case, the first category. Then, the density function for the category is estimated 703. More specifically, the parameters for the density function for the selected category are estimated from the training data structure (FIG. 11). For example, in the case where a Gaussian density function is used, the mean for each selected feature (FIG. 11) and the variance-covariance matrix for these features are estimated within

> each category (FIG. 11). These estimates become the parameter values in the estimated Gaussian density function for each category. In this estimated Gaussian density function, there exists a variable for each selected feature. The thusly created estimated density function is stored 705. Then, the estimated density function for the selected category is used to calculate an estimated relative density value for the selected individual in the selected category 707. More specifically, using the foregoing example, the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained. The result is used to create a density value data structure, which is stored 709. Then a test 711 is made to determine if any more categories exist. If more categories exist, the process is repeated. As will be recalled, the process illustrated in FIG. 7 occurs after the training data structure has been updated by removing a selected individual from a selected category. Thus, the density value data structure is for a selected individual in a selected category with the n individuals' data removed. An example of a density value data structure is shown in FIG. 12. For each category 1211 an estimate of the likelihood that each individual 1213 will fall in each category 1215a, 1215b . . . 1215n is included in the data structure.

Applicants' attorney notes that the cited location in Cook merely describes a training process, but says nothing about estimating a Coefficient for each of the identified related independent and dependent variables. Moreover, as noted above, a density function is not a Transformation Type. In addition, the scalar referred to above is the result of the density function, whereas the Coefficient is a weight, for each of the identified related independent and dependent variables found to be significant in predicting the likelihood of response. Specifically, the Coefficient is a relative measure of the contribution of a variable to the likelihood of response, wherein the sign of the Coefficient indicates whether the independent variable is positively or negatively correlated with the dependent variable.

In another example, the Office Action asserts that Cook teaches "(f) generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient," i.e., a Gaussian density function, at col. 13, lines 5-45, which are set forth above in conjunction with element (e).

Applicants' attorney again notes that a density function is not a Transformation Type and a Coefficient is a relative measure of the contribution of a variable to the likelihood of response. Consequently, Cook does not describe generating the same Model Equation as recited in Applicants' claims.

In yet another example, the Office Action asserts that Cook teaches "(g) validating the generated Model Equation by applying it to the validation sample," i.e., calibration, at col. 11, lines 5-20, which are set forth below:

> After the training process 411 is completed, a calibration process 413 is performed. An example of a calibration process formed in accordance with the invention is illustrated in FIG. 8 and described below. The calibration process creates a decision array in which are stored the results of classifying the individuals whose individual profile features were contained in the training sample. As will be better understood from the following description, the decision array compares an individual's true category to the category predicted by the selected inference engine. The decision array in combination with the estimated density function and density value data structure contain all the algorithms and parameters necessary for implementation of the selected engine.

Applicants' attorney notes that the cited location in Cook merely describes a calibration process using the training sample, but says nothing about validating the generated Model Equation by applying it to a validation sample that is created by splitting an input data set into a test sample and a validation sample.

In still another example, the Office Action asserts that Cook teaches "(h) scoring customers retrieved from a database using the validated Model Equation," i.e., a scalar is obtained, at col. 13, lines 25-35 and FIG. 12, which are set forth below:

> As noted above, FIG. 7 illustrates a density function and density value calculating process 605 suitable for use in the process illustrated in FIG. 6 formed in accordance with the invention. First, a category is selected 701 by, for example, setting a pointer to the memory location of the data associated with the selection--in this case, the first category. Then, the density function for the category is estimated 703. More specifically, the parameters for the density function for the selected category are estimated from the training data structure (FIG. 11). For example, in the case where a Gaussian density function is used, the mean for each selected feature (FIG. 11) and the variance-covariance matrix for these features are estimated within each category (FIG. 11). These estimates become the parameter values in the estimated Gaussian density function for each category. In this estimated Gaussian density function, there exists a variable for each selected feature. The thusly created estimated density function is stored 705. Then, the estimated density function for the selected category is used to calculate an estimated relative density value for the selected individual in the selected category 707. More specifically, using the foregoing example, the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained. The result is used to create a density value data structure, which is stored 709. Then a test 711 is made to determine if any more categories exist. If more categories exist, the process is repeated. As will be recalled, the process illustrated in FIG. 7 occurs after the training data structure has been updated by removing a selected individual from a selected category. Thus, the density value data structure is for a selected individual in a selected category with the n individuals' data removed. An example of a density value data structure is shown in FIG. 12. For each category 1211 an estimate of the

likelihood that each individual 1213 will fall in each category 1215a, 1215b . . . 1215n is included in the data structure.

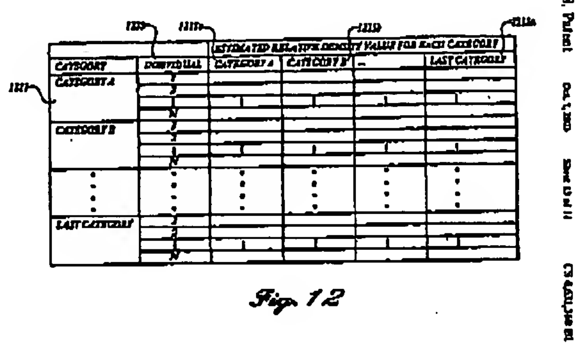

Fig. 12

Applicants' attorney notes that the cited location in Cook merely describes using an estimated density function for a selected category to calculate an estimated relative density value for a selected individual in the selected category. However, as noted above, a density function is not a Transformation Type and the results of a density function are not a Coefficient. Thus, Cook does not describe the same Model Equation as recited in Applicants' claims. Consequently, Cook does not score customers using the validated Model Equation as a customer promotion response model for use in customer relationship marketing.

In light of the above, Applicants' attorney submits that independent claims 1, 8, and 15 are allowable over Cook. Further, dependent claims 2-7, 9-14, and 16-21 are submitted to be allowable over Cook in the same manner, because they are dependent on independent claims 1, 8, and 15, respectively, and thus contain all the limitations of the independent claims. In addition, dependent claims 2-7, 9-14, and 16-21 recite additional novel elements not shown by Cook.

VII. Conclusion

In view of the above, it is submitted that this application is now in good order for allowance and such allowance is respectfully solicited.

Should the Examiner believe minor matters still remain that can be resolved in a telephone interview, the Examiner is urged to call Applicants' undersigned attorney.

Respectfully submitted,

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